IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17011

Ambient Air Pollution and Helping Behavior: Evidence from the Streets in Beijing

Simon Chang
Ishita Chatterjee
Li Yu

MAY 2024

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17011

Ambient Air Pollution and Helping Behavior: Evidence from the Streets in Beijing

Simon Chang
University of Western Australia and IZA

Ishita Chatterjee
University of Western Australia

Li Yu
Central University of Finance and Economics

MAY 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Ambient Air Pollution and Helping Behavior: Evidence from the Streets in Beijing

We conducted a large-scale lost letter experiment with a novel design across all seasons in Beijing to study whether ambient air pollution influences helping behavior. We assessed air pollution by PM2.5 and PM10. Our novel design allowed us to collect real-time granular data from the streets. To mitigate endogeneity bias, we used the occurrence and intensity of thermal inversion as instrumental variables. We found that ambient air pollution increased the probability for a lost letter to be posted. Our finding suggests that when exposed to ambient air pollution, individuals may cope with the resulting adverse mental states by helping others.

JEL Classification: D9, Q5

Keywords: air pollution, helping behavior, particulate matter, thermal inversion, China

Corresponding author:
Simon Chang
University of Western Australia
35, Stirling Highway
Crawley, 6009, WA
Australia

E-mail: simon.chang@uwa.edu.au

1. Introduction

Along the process of industrialization and urbanization, the combustion of fossil fuels and biomass has led to the permeation of air pollution through the fabric of our daily lives. According to the World Health Organization (WHO), 99% of the world population is exposed to air pollution, with disproportionate impacts on individuals in developing countries (World Health Organization, 2021). Extensive evidence has shown that air pollution is a leading cause of mortality and mobidity around the world (Chen and Hoek 2020; Dominski, et al., 2021). Beyond its well-established health consequences, recent research has also revealed that air pollution is detrimental to our cognitive performance (Ebenstein et al., 2016; Zhang et al., 2018), decision-making (Burkhardt et al., 2019; Sager, 2019; Bondy et al., 2020; Huang et al., 2020; Chew et al., 2021; Dong et al., 2021; Herrnstradt et al., 2021), and productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Lichter et al., 2017; Guo and Fu, 2019; He et al., 2019; Fu et al., 2021).[1]

Nevertheless, our understanding of whether air pollution influences human prosocial behavior is still limited, despite the crucial role prosocial behavior plays in upholding human society. This paper focuses on one type of prosocial behavior—helping or acts that benefit others. This inquiry is prompted by a growing body of research connecting air pollution to human mental well-being. Specifically, air pollution has been found to cause various negative psychological effects such as stress, annoyance, anxiety, depression (Mehta, et al., 2015; Zhang, et al., 2021; Lu, 2020). We argue that these psychological effects could further influence helping behavior for the following reason.

Social psychologists have long suggested that one of the main drivers for prosocial action is the egoistic motive, i.e., helping others to secure personal gain (Cialdini and Kenrick, 1976; Cialdini, et al., 1981; Buchanan and Preston, 2014; Schroeder and Graziano,

[1] For recent reviews of non-health effects, refer to Lu (2020) and Aguilar-Gomez et al. (2022).

2014). This is parallel to the theory of warm-glow giving in economics (Andreoni, 1990). In the context of air pollution, individuals exposed to air pollution may be motivated to help others if helping leads to good feelings about themselves or praise from others, both of which in turn could remove or ameliorate the stress and other negative mental states resulting from air pollution exposure. In other words, helping could work as a coping mechanism (Midlarsky, 1991).

Beyond the theories, numerous recent empirical studies in neuroscience and psychology have also found supporting evidence linking negative mental states to prosocial behavior. For example, Vinkers et al. (2013) found that participants in the Ultimatum Game showed greater altruistic punishment immediately after being exposed to a stressor. Pérez-Dueñas et al. (2018) showed that induced negative mood increased giving in the Dictator Game. Vieira et al. (2022) discovered that individuals' perceived threat of COVID-19 and anxiety were associated with their increased altruistic behavior. Moreover, Raposa et al. (2016) demonstrated that engaging in prosocial behavior can mitigate the negative effects of stress.

Motivated by these studies, we tested the causal link between ambient air pollution and helping behavior by conducting a large-scale lost letter experiment with a novel design across all seasons in Beijing, China. We dropped ready-to-be-posted letters across the city on the footpath in front of a letterbox for passersby to pick up. In this experiment, helping behavior refers to the action of posting the lost letter because it benefits the recipient and sender of the lost letter. It is worth noting that picking up the letter without posting it is not considered as helping. Also, posting the letter is unlikely to be driven by a reciprocal motive because both the recipient and sender are unknown strangers to the passersby.

We carried out the experiment in nine locations across the city, each of which is in the proximity of an air pollution monitoring station from where real-time air pollution readings were acquired. To assess the air pollution levels, we used hourly concentration readings of both fine particulate matter (PM2.5, particles with an aerodynamic diameter equal to or less than 2.5 micrometers) and coarse particulate matter (PM10, particles with an aerodynamic diameter equal to or less than 10 micrometers). The use of real-time air pollution readings renders our estimates the acute effect of air pollution on helping behavior. As such, the long-term effect of air pollution is beyond the scope of this paper.

Unlike the conventional lost letter experiment, which only observes the returned lost letters, we made additional efforts to collect a rich set of real-time information by staying at the location after dropping the letters to record the time that each letter was dropped and removed, and whether the letter was picked up and posted on site. This not only allows us to link the outcomes to real-time air pollution readings but also to measure the time that it took to be removed. In addition, we recorded the number of men and women who passed by before the letter was removed, and the ambient noise and temperature using software installed on a smartphone. These additional data help us further investigate how foot traffic, the gender composition of passersby, and other environmental factors affect the outcomes of the lost letters and allow us to control for these heterogeneities across locations and time in our regression analysis. Particularly, researchers have noted that noise is an important confounder in studying the air pollution effect on mental health (Braithwaite, et al., 2019).

One might be concerned that air pollution may change the composition of passersby on the street and lead to a sample selection bias if selfish individuals were more inclined to avoid air pollution than their altruistic counterparts. However, we found no basis to suggest that altruistic individuals, who genuinely care more about others, should care less about their own health and exhibit less avoidance behavior compared to selfish individuals. As an indirect test, we compared our experimental results during weekdays against weekends because people generally have more flexibility to exercise avoidance during weekends. As predicted, we found no significant difference between the two periods in a week.

Due to both ethical and technical reasons, we were unable to randomly manipulate air pollution exposure, implying that our experimental results were subject to potential bias from still unobserved confounders. For instance, traffic could affect both ambient air pollution and the mental states of people walking on the street. Meanwhile, different locations may have other unobserved characteristics, e.g. local economic activities, types of residents, that could be related to both air pollution and people's behavior. To mitigate the potential bias, we adopted the following econometric methods. First, to adjust for time-invariant location-specific unobserved confounders as well as common seasonal factors across locations, we added a full set of location and seasonal fixed effects in all regressions. Nonetheless, these fixed effects could not capture confounders that varied across time and locations such as traffic.

To address this concern, we followed previous studies to use thermal inversion to instrument for air pollution (Arceo et al., 2015; Jans et al., 2018; He et al., 2019; Sager, 2019; Fu et al., 2021; Chen et al., 2023). Air temperature in the troposphere, the lowest layer of the Earth's atmosphere in direct contact with the Earth's surface, usually declines along with altitude. Thermal inversion refers to an occasional phenomenon in the troposphere that a layer of warm air sits on top of a layer of cool air. In other words, the drop in air temperature reverses when the altitude reaches the layer of warm air. The layer of warm air works as a lid that prevents air pollutants from dispersing vertically, forcing them to accumulate at the surface level.

Vertical dispersion is particularly critical in Beijing because horizontal movement of air is limited by the mountains surrounding its west, north and northeast. Wang et al. (2019) showed that not only the occurrence of thermal inversion but also its intensity is positively correlated with PM2.5 concentrations in Beijing during winter. Hence, we also measured the intensity by taking the difference in temperature at the bottom and top of the inversion layer and used it as an additional instrumental variable conditional on the occurrence of the inversion.

We controlled for other meteorological variables at the surface such as temperature, wind speed, humidity and air pressure that are correlated with air pollution and likely affect people's mental states, too. Conditional on these meteorological variables at the surface, we argue that thermal inversion itself does not directly affect the helping behavior of people on the streets. We thus applied the two-stage least square (2SLS) estimation method to mitigate the potential bias resulted from the non-randomness of air pollution. Moreover, the 2SLS method also mitigates a potential bias resulted from measurement errors in PM2.5 and PM10, although we think measurement errors should be minimal as we obtained the readings directly from nearby air pollution monitoring stations.

Our OLS results show that PM10 is positively correlated with the probability of posting the lost letter. A one-standard-deviation increase in PM10 is associated with an increase in the probability by about four percentage points. In contrast, the estimate for PM2.5 is only one percentage point and statistically insignificant. We also estimated a non-linear model and found that higher quartiles in the PM10 distribution tend to have larger effects than lower quartiles. Nonetheless, results for PM2.5 do not show significant differences between quartiles.

After addressing the endogeneity issue with the instrumental variables, our 2SLS estimates of the linear effects are larger and statistically significant for both PM2.5 and PM10. When both instrumental variables are used, the effects are 16 and 14 percentage points for a one-standard-deviation increase in PM2.5 and PM10 respectively. To the best of our knowledge, these findings provide the first causal evidence that air pollution exposure increases helping behavior. It is also worth noting that the endogeneity issue appears to be worse for PM2.5 given that the gap between its OLS and 2SLS estimate is substantially wider than PM10.

To provide supporting evidence on the psychological mechanism, we used search data from the largest search engine in China, Baidu.com (百度). We compared the search popularity in four major Chinese cities, Beijing (北京), Shanghai (上海), Guangzhou (广州) and Shenzhen (深圳), during 2017-2023 for “air pollution” (空气污染) and three negative mental effects, “stress” (压力), “anxiety” (焦虑), and “depression” (抑郁) against PM2.5 and PM10 concentrations respectively. The search interest for “air pollution” is strongly and positively correlated with PM2.5 and PM10, indicating that when it was more polluted, people did more searches on air pollution. As for the searches for the three negative mental states, the correlations are also positive, although the correlations with PM10 appear to be slightly stronger. These correlations between people’s internet search interests and air pollution are consistent with the psychological mechanism. We provide more discussion on mechanisms in section four.

The rest of this paper is organized as follows. Section two describes the experiment design in detail. Section three summarizes the data and reports the experiment results. Section four discusses potential mechanisms. Section five concludes the paper.

2. Experiment Design

2.1 *The Lost Letters Technique*

The lost letter technique was originally devised by Stanley Milgram in 1965 and has been adopted to study helping behavior in social psychology (Milgram, Mann, and Harter 1965). The technique involves dropping stamped and ready-to-be-posted letters in public areas for passersby to pick up and measuring the helping behavior by the return rate of the lost letters. This technique allows researchers to detect what factors determine people’s helping behavior usually by varying the information appearing on the envelope such as the recipient or the address. Unlike the conventional lost letter technique, our treatment is the air pollution that varied across areas and time. As mentioned, we were unable to randomly manipulate air pollution. As such, we instrumented air pollution with thermal inversion and adopted the 2SLS estimate method.

In our experiment, the information on the envelope included the name of a fictional recipient and a post office box number as the address, both of which were respectively written in simplified Chinese. Inside the envelope was a typed generic letter. On the back of the envelope was a unique code that allowed us to identify the date, time, and location. We dropped letters on the footpath in front of letterboxes in nine locations in Beijing. On each day in each location, we dropped a total of three letters every hour in 9AM, 10AM and 11AM. Each letter was left on the ground for a maximum of ten minutes unless it was removed earlier. If the letter had not been removed after ten minutes, we retrieved it and then dropped another letter. This design is to increase the power by increasing the observations for each hourly reading of air pollution in each location. To account for the same reading for three letters, we clustered robust standard errors at the location-hour level in our regression analysis.

We carried out four waves of experiments in Beijing, with each wave taking place in a distinct season. Experiments were conducted for five days during each wave. Specifically, the four waves took place on 1) 22−25 and 27 September 2017 (autumn); 2) 6−7 and 9−11 May 2018 (spring); 3) 11−15 January 2019 (winter); and 4) 14−18 July 2019 (summer).[2] In total, we dropped 1,620 letters in Beijing. One observation was discarded due to a violation of our experiment protocol. Hence, the final sample of analysis consisted of 1,619 observations.

[2] The dates in each wave are not necessarily consecutive. In some cases, the experiment had to be cancelled because of rain.

What made our technique novel is that we stayed to observe after dropping each letter. This allowed us to collect a rich set of real-time information. We recorded the time the letter was dropped and the time it was removed. As for outcomes, we observed whether it was picked up and posted into the nearby letterbox. In addition, we collected a wealth of information regarding the surrounding environment. Specifically, we counted the number of men and women who passed the letter within a three-meter radius until it was picked up. We also measured the noise and temperature using software installed on a smartphone.

2.2 *Air Pollution Monitoring Stations*

We collected PM2.5 and PM10 data from nine air pollution monitoring stations in Beijing (Figure 1). To maximize the covered area within logistical feasibility, we chose stations that all our team members could travel to carry out the experiment and return at around the same time within our budget. The nine stations in Beijing scatter across six districts of the inner city, while the entire city of Beijing has sixteen districts.

All these stations consistently reported PM2.5 readings during our experiments, but a small fraction of PM10 readings were not reported. Thus, about 7% of the observations in Beijing could not be matched with PM10 readings due to non-reporting. We conducted a robust check of our results and concluded that the missing values did not systematically bias our estimates.[3] The monitoring stations update air pollution data by the hour.

2.3 *Student Recruitment, Training, and Pilot Experiments*

We recruited graduate students from the Central University of Finance and Economics in Beijing. The students were first briefed on the details of the experiment. They later helped locate suitable dropping locations in the proximity of the monitoring stations

[3] We estimated the PM2.5 effect by excluding the observations that PM10 reading were missing. The estimate of the PM2.5 remains very similar. The result is available upon request.

where street letterboxes were present. During the experiment, a pair of students was assigned to take charge of all the tasks in each location.

The students attended a training session where they learned how to carry out various tasks including preparing the letters, stealthily dropping, and collecting the letters, counting the passersby by gender, measuring the noise and temperature, and recording all the information in a worksheet. They were taught how to act as a passerby without raising suspicions. At last, all the data that each pair collected from the field were sent to a coordinator, who then compiled all the data. The coordinator was also responsible for collecting the real-time PM2.5 and PM10 readings from the air pollution monitoring stations. The students took part in a pilot experiment during March 18−19, 2017 to practice letter dropping, recording observations, and noting potential issues.

3. Data and Experiment Results

3.1 *MERRA-2 Data*

Our thermal inversion data and other meteorological variables at the surface come from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) from the Global Model and Assimilation Office (GMAO) at National Aeronautics and Space Administration (NASA). MERRA-2 maps the entire globe onto a grid with 576 longitudinal points and 361 latitudinal points. Each cell in the grid is approximately 50km×50km. This implies that all our experiment locations are clustered in one cell. As a result, we can only utilize the temporal variation in thermal inversion and other meteorological variables at the surface. Nevertheless, the temporal variations in PM2.5 and PM10 in our data are also 5 to 6 times larger than the geographic variations.

The specific MERRA-2 products we used are ins3_3d_asm_Np and inst1-2d_1fo_Nx. The first product provides vertical air temperature readings at 42 air pressure levels every three hours each day starting from 00:00 UTC (08:00 Beijing time). Our letters were dropped in the hours of 9 AM, 10 AM and 11 AM in Beijing time. We matched the 9-10 AM letters to the 00:00 UTC readings and the 11 AM letters to the 03:00 UTC readings.[4] We calculated the corresponding altitude for each air pressure level and then determine the altitude of thermal inversion if it occurred. Following Chen et al. (2023), we constructed a dummy variable to indicate whether thermal inversion occurred at or below 320 meters.[5] To measure the intensity, we calculated the temperature gradient by taking the difference between the temperature at the bottom of the inversion layer to that at the top. It is worth noting that if there were multiple inversions at different altitudes at the same time, we only considered the lowest inversion because it was the most relevant one in trapping the pollutants at the surface level.

The second product offers data on specific humidity, wind speed, air pressure at the surface level for each hour in a day. Specific humidity is the ratio of the mass of water vapor in a unit of air mass. Wind speed is measured in meters per second. Air pressure is measured in Pascal. This product also reports surface temperature. However, we decided to use the temperature data that we collected from our experiment since it has both geographic and temporal variation.

3.2 *Summary Statistics*

Figure 2 illustrates the distribution of the PM2.5 and PM10 concentration readings by wave. Please note that they are the readings matched with our letters dropped in each wave of experiment. They are not to be confused with the actual seasonal distributions of the two particulate matters in Beijing. As shown, winter appears to be the worst season for PM2.5 followed by spring. In terms of PM10, the most polluted season is spring and then autumn. In Table 1, the mean of PM2.5 and PM10 are 60 μg/m^3 and 110 μg/m^3. For reference, the WHO

[4] We also tried matching the 9AM letters to the 00:00UTC readings and 10-11AM letter to the 03:00UTC readings. The results are similar and available upon request.
[5] We also tried alternative definitions at 380 meters and 400 meters. The results remain robust and available upon request.

air quality guideline recommends that the average 24-hour level of PM2.5 and PM10 should be less than 15 μg/m^3 and 45 μg/m^3 respectively (WHO 2021).

Also shown in Table 1, about 72% of letters were picked up within 10 minutes, but only 36% were posted. It took an average of slightly less than 6 minutes for a letter to be picked up. On average, before each letter was picked up, 28 people had passed with an almost perfect balance of gender. About 7% of the letters were dropped when thermal inversion occurred at 320 meters or below. When the inversion occurred, the average change in temperature is about 1.6 °C.

3.3 *Regression Specifications*

We adopted the following linear probability models with fixed effects.

$$y_{iwc} = \beta_0 + \beta_1 stdPM_{iwc} + BX_{iwc} + \delta_w + \tau_c + \varepsilon_{iwc}, \tag{1}$$

where y_{iwc} is a dummy variable indicating whether letter *i* in season *w* in location *c* was posted; *stdPM* is the standardized PM2.5 or PM10 with mean zero and standard deviation equal to one; *B* is a row vector of coefficients corresponding to the column vector *X*, which consists of ambient noise, temperature, surface windspeed, specific humidity, air pressure, number of passersby per minute and percentage of women among passersby; δ and τ represent fixed effects for wave and location; ε is the error term. We used robust standard errors clustered at the location-date-hour level for statistical inferences.

We standardized the PM2.5 and PM10 by subtracting them by the sample mean and then dividing them by the standard deviation. This was to allow the coefficient β_1 to represent the change in the probability of the letter being posted in response to one standard deviation change in either PM2.5 or PM10.

Equation (1) estimates the linear effect of the particulate matter. To introduce non-linearity, we replace the standardized particulate matter variable with two dummy variables indicating the third and fourth quartiles of the distribution of each particulate matter.

For 2SLS estimation, the specification of the first stage regression is as follows.

$$stdPM_{iwc} = \alpha_0 + \alpha_1 Inversion_{iwc} + \alpha_2 TempDiff_{iwc} + AX_{iwc} + \theta_w + \rho_c + \mu_{iwc}, \qquad (2)$$

where *Inversion* is a dummy variable equal to one if an inversion occurred at 320 meters or below; *TempDiff* is the change in temperature between the bottom and top of the inversion layer and zero if there was no inversion; *A* is a row vector of coefficients corresponding to the same column vector *X* as in equation (1); θ and ρ represent fixed effects for wave and location; μ is the error term.

3.4 *OLS Estimates*

We first report the linear results in Table 2. As shown, estimates of both particulate matters are positive. However, only the PM10 estimate is statistically significant. Specifically, a one-standard-deviation increase in PM10 is associated with a higher probability for a lost letter to be posted by nearly 4 percentage points. The same increase for PM2.5 is only associated with a much smaller increase of 1 percentage point, and it is not even statistically significant.

Table 2 also allows us to examine how the composition of passersby and other environmental indicators affect helping behavior. It appears that foot traffic is positively correlated with posting the lost letter. Specifically, one more passerby per minute increases the probability by 1.3 percentage points. Moreover, specific humidity is negatively correlated with the probability. Other than these two variables, we do not find any other variable matters in this context.

Table 3 show some evidence of non-linearity. Particularly, the higher quartiles of PM10, the larger the effects. Respectively, the 4th and 3rd quartile effects are 11 and 10 percentage points higher than the bottom two quartiles. In contrast, the non-linear effects of PM2.5 are trivial and statistically insignificant, suggesting no discernible difference between the quartiles. Overall, both linear and non-linear estimates show a positive and significant correlation between PM10 and helping behavior.

3.4 *OLS Estimates between Weekdays and Weekends*

As mentioned, we do not find any basis for people's avoidance behavior in response to air pollution to be correlated with their helping behavior. Still, we check this possibility by comparing the OLS estimates between weekdays and weekends by adding a dummy variable indicating weekends and interacting it with the particulate matter variable. This is because people usually have a greater flexibility to avoid walking on the street during the weekend. If avoidance was related to helping behavior, the interaction between the weekend dummy and the particulate matter should be positive and statistically significant. Nevertheless, none of the interaction terms in Table 4 is significant.

3.5 *2SLS Estimates*

Table 5 reports the 2SLS estimates of the linear effect of particulate matters. Unlike the OLS estimates, the second-stage results in Panel A show that both PM2.5 and PM10 are statistically significant and much larger. The effect of a one-standard-deviation increase in PM2.5 is about 22 and 16 percentage points corresponding to when only one and both instruments are used respectively. For PM10, they are 13 and 14 percentage points respectively. An alternative interpretation is to use an increase of 10 $\mu g/m^3$. Since the standard deviation in PM2.5 and PM10 are different, their magnitudes are also different. Specifically, an increase of 10 $\mu g/m^3$ in PM2.5 leads to an increase in the probability by 5 to 7 percentage points, while the same increase in PM10 only leads to an increase of 2 to 3 percentage points.

In Panel B, the first-stage results show that both the occurrence and intensity of thermal inversion increase the particulate matters. The Kleibergen-Paap *F* statistics suggest that the two instrumental variables are strong instruments. In the cases of using both instrumental variables, we also conducted the overidentification test. The Hansen *J* statistics show that they are both valid instruments.

4. Potential Mechanisms

We have argued that the pathway for air pollution to affect helping behavior is through mental well-being. That is, individuals cope with their negative mental states resulting from air pollution by helping others. Although we have discussed the literature linking air pollution to mental well-being and that linking mental well-being to prosocial behavior, here we add another novel supporting evidence on the first link. We studied people's internet search interests in four major cities in China, Beijing (北京), Shanghai (上海), Guangzhou (广州) and Shenzhen (深圳), by using data from the largest search engine in China, Baidu.com (百度). These four cities are collectively known as the first-tier cities. We plotted the monthly search popularity during 2017-2023 for "air pollution" (空气污染), "stress" (压力), "anxiety" (焦虑), and "depression" (抑郁) against corresponding monthly concentration of PM2.5 and PM10 in Beijing, which came from the World Air Quality Index Project.

As shown in Figure 3, the search interest for "air pollution" is strongly and positively correlated with both PM2.5 and PM10. Meanwhile, searches for the three negative mental states also exhibit a generally positive correlation with the two pollutants, especially with PM10. While we are aware that these positive correlations are not causal, they do suggest that people are more likely to search for these key words when air pollution gets worse. To trigger people to search for "air pollution," the most likely channel is that the pollutants enhance people's perception or awareness of air pollution in their surrounding environment. Similarly, people's search interests for the negative mental states are very likely motivated by personal psychological experiences, which are likely rooted in their perception of air pollution. All these observations are consistent with the psychological mechanism.

An alternative mechanism could be physiological. Once they enter the body, air pollutants can possibly affect the brain and various hormones that regulate a wide range of human social behavior. Yet, this physiological mechanism is very complex and is not well understood (Weitekamp and Hoffmann 2021). In addition, air pollutants must be extremely small to penetrate the lung barrier and enter the blood system before they can manipulate our brains and hormones. Up to date, scientific evidence shows that only PM2.5 can penetrate the lung barriers (Peters et al. 2006). If it was the physiological mechanism, we should have observed more consistent evidence from PM2.5 but not from PM10. However, the comparison between the OLS and 2SLS results shows that PM10 seems to suffer less of the endogeneity bias than PM2.5. We thus lean toward the psychological mechanism.

5. Conclusion

We estimated the causal effect of air pollution on helping behavior by conducting a large-scale lost letter experiment in Beijing and instrumenting air pollution with thermal inversion. We provided the first causal evidence to show that air pollution increases helping behavior. Nevertheless, it would be imprudent to hastily attribute it as a direct benefit of air pollution. Rather, our study sheds light on the intricate interplay between environmental factors and human behavior, emphasizing the necessity for further research to dig out more direct evidence on the underlying mechanisms. By delving deeper into this complex relationship, we can gain a more nuanced understanding of the implications and potentially develop more effective strategies to mitigate the adverse effects of air pollution on both the environment and human well-being.

References

Aguilar-Gomez, Sandra, Holt Dwyer, Joshua S. Graff Zivin, and Matthew J. Neidell. 2022. "This is Air: The 'Non-health' Effects of Air Pollution." *NBER Working Paper* no. 29848.

Andreoni, James. 1990. "Impure Altruism and Donations to Public Goods, A Theory of Warm-Glow Giving." *The Economic Journal* 100 (401): 464-477.

Arceo, Eva, Rema Hanna, and Paulina Oliva. 2015. "Does the Effect of Pollution on Infant Mortality Differ between Developing and Developed Countries? Evidence from Mexico City." *The Economic Journal*, 126: 257-280

Bondy, Malvina, Sefi Roth, and Lutz Sager. 2020. "Crime is in the Air: The Contemporaneous Relationship between Air Pollution and Crime." *Journal of the Association of Environmental and Resource Economists* 7 (3): 555-585.

Braithwaite, Isobel, Shuo Zhang, James B. Kirbride, David P. J. Osborn, and Joseph F. Hayes. 2019. "Air Pollution (Particulate Matter) Exposure and Associations with Depression, Anxiety, Bipolr, Psychosis and Suicide Risk: A Systematic Review and Meta-Analysis." *Environmental Health Perspectives* 127(12): 126002.

Buchanan, Tony W., and Stephanie D. Preston. 2014. "Stress Leads to Prosocial Action in Immediate Need Situations." *Frontiers in Behavioral Neuroscience* 8 (5): 1-6.

Burkhardt, Jesse, Jude Bayham, Ander Wilson, Ellison Carter, Jesse D. Berman, Katelyn O'Dell, Bonne Ford, Emily V. Fischer, and Jeffry R. Pierce. 2019. "The Effect of Pollution on Crime: Evidence from Data on Particulate Matter and Ozone." *Journal of Environmental Economics and Management* 98: 102267.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2016. "Particulate Pollution and the Productivity of Pear Packers." *American Economic Journal: Economic Policy* 8 (3): 141-169.

Chen, Jie, and Gerard Hoek. 2020. "Long-term Exposure to PM and All-cause and Cause-specific Mortality: A Systematic Review and Meta-analysis." *Environment International* 143:105974.

Chen, Xiaoguang, Luoye Chen, Wei Xie, Nathaniel D. Mueller, and Steven J. Davis. 2023. "Flight Delays Due to Air Pollution in China." *Journal of Environmental Economics and Management*, 119: 102810.

Chew, Soo H., Wei Huang, and Xun Li. 2021. "Does Haze Cloud Decision Making? A Natural Laboratory Experiment." *Journal of Economic Behavior and Organization* 182: 132-161.

Cialdini, Robert, B., Donald J. Baumann, and Douglas T. Kenrick. 1981. "Insights from Sadness: A Three-Step Model of the Development of Altruism as Hedonism." *Developmental Review* 1: 207-223.

Cialdini, Robert, B., and Douglas T. Kenrick. 1976. "Altruism as Hedonism: A Social development Perspective on the Relationship of Negative Mood State and Helping." *Journal of Personality and Social Psychology* 34(5): 907-914.

Dominski, Fábio Hech, Joaquim Henrique Lorenzetti Branco, Giorgio Bunanno, Luica Stabile, Manuel Gameiro da Silva, and Alexandro Andrade. 2021. "Effects of Air Pollution on Health: A Mapping Review of Systematic Reviews and Meta-analyses." *Environmental Research* 201, 111487.

Dong, Rui, Raymond Fisman, Yongxiang Wang, and Nianhang Xu. 2021. "Air Pollution, Affect, and Forecasting Bias: Evidence from Chinese Financial Analysts." *Journal of Financial Economics* 139 (3): 971-984.

Ebenstein, Avrahan, Victor Lavy, and Sefi Roth. 2016. "The Long-run Economic Consequences of High-stakes Examinations: Evidence from Transitory Variation in Pollution." *American Economic Journal: Applied Economics* 8 (4): 36-65.

Fu, Shihe, V. Brian Viard, and Peng Zhang. 2021. "Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China." *The Economic Journal*, 131: 3241-3273.

Graff Zivin, Joshua, and Matthew Neidell. 2012. "The Impact of Pollution on Worker Productivity." *American Economic Review* 102 (7): 3652-3673.

Guo, Mengmeng, and Shihe Fu. 2019. "Running with a Mask? The Effect of Air Pollution on Marathon Runners' Performance." *Journal of Sports Economics* 20 (7): 903-928.

He, Jiaxiu., Haoming Liu, and Alberto Salvo. 2019. "Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China." *American Economic Journal: Applied Economics* 11 (1): 173-201.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian. 2021. "Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago." *American Economic Journal: Applied Economics* 13 (4): 70-100.

Huang, Jeikun, Nianhang Xu, and Honghai Yu. 2020. "Pollution and Performance: Do Investors Make Worse Trades on Hazy Days?" *Management Science* 66 (10): 4455-4476.

Jans, Jenny, Per Johansson, and J. Peter Nilsson. 2018. "Economic Status, Air Quality, and Child Health: Evidence from Inversion Episodes." *Journal of Health Economics*, 61: 220-232.

Lichter, Andreas, Nico Pestel, and Eric Sommer. 2017. "Productivity Effects of Air Pollution: Evidence from Professional Soccer." *Labour Economics* 48: 54-66.

Lu, Jackson G. 2020. "Air Pollution: A Systematic Review of its Psychological, Economic and Social Effects." *Current Opinion in Psychology* 32: 52-65.

Mehta, Amar J., Laura D. Kubzansky, Brent A. Coull, Itai Kloog, Petros Koutrakis, David Sparrow, Avron Spiro III, Pantel Vokonas, and Joel Schwartz. 2015. "Associations between Air Pollution and Perceived Stress: The Veterans Administrative Normative Aging Study." *Environmental Health* 14:10, doi: 10.1186/1476-069X-14-10. PMID: 25627872; PMCID: PMC4417295.

Midlarsky, Elizabeth. 1991. "Helping as Coping." In *Prosocial Behavior*, edited by Margaret S. Clark, 238-264, Sage Publications, Inc.

Milgram, Stanley, Leon Mann, and Susan Harter. 1965. "The Lost-letter Technique: A Tool of Social Research." *Public Opinion Quarterly* 29: 437–438.

Pérez-Dueñas, Carolina, M. Fernanda Rivas, Olusegun A. Oyediran, and Francisco Garcia-Torres. 2018. "Induced Negative Mood Increases Dictator Game Giving." *Frontiers in Psychology*. 9:1542.

Peters, Annete, Bellina Veronesi, Lilian Calderćon-Garcidueñas, Peter Gehr, Lung Chi Chen, Marianne Geiser, William Reed, Barbara Rothen-Rutishauser, Samuel Schürch, and Holger Schulz. 2006. "Translocation and Potential Neurological Effects of Fine and Ultrafine Particles a Critical Update." *Particle and Fibre Toxicology* 3 (13).

Raposa, Elizabeth B., Holly B. Laws, and Emily B. Ansell. 2016. “Prosocial Behavior Mitigates the Negative Effects of Stress in Everyday Life.” *Clinical Psychological Science* 4(4): 691-698.

Sager, Lutz. 2019. “Estimating the Effect of Air Pollution on Road Safety Using Atmospheric Temperature Inversions.” *Journal of Environmental Economics and Management* 98:102250.

Schroeder, David A., and William G. Graziano. 2014. The Field of Prosocial Behavior: An Introduction and Overview. In D. A. Schroeder, & W. G. Graziano, *The Oxford Handbook of Prosocial Behavior*. (pp. 3-34). New York: Oxford University Press.

Vieira, Joana, Stephen Pierzchajlo, Simon Jangard, Abigail A. Marsh, and Andreas Olsson. 2022. “Acute Anxiety During the COVID-19 Pandemic Was Associated with Higher Levels of Everyday Altruism.” *Scientific Reports* 12:18619.

Vinkers, Christian H., Jelle V. Zorn, Sandra Cornelisse, Susanne Koot, Lotte C. Houtepen, Berend Olivier, Joris C. Verster, Rene S. Kahn, Marco P.M. Boks, Tobias Kalenscher, and Marian Joëls. 2013. “Time-dependent Changes in Altruistic Punishment Following Stress.” *Psychoneuroendocrinology* 38: 1467-1475.

Wang, Linlin, Hong Wang, Junkai Li, Zhiqiu Gao, Yuanjian Yang, Xiaoye Zhang, Yubin Li, and Meng Huang. 2019. “Impacts of the Near-surface Urban Boundary Layer Structure on PM2.5 Concentrations in Beijing during Winter.” *Science of the Total Environment*, 669: 493-504.

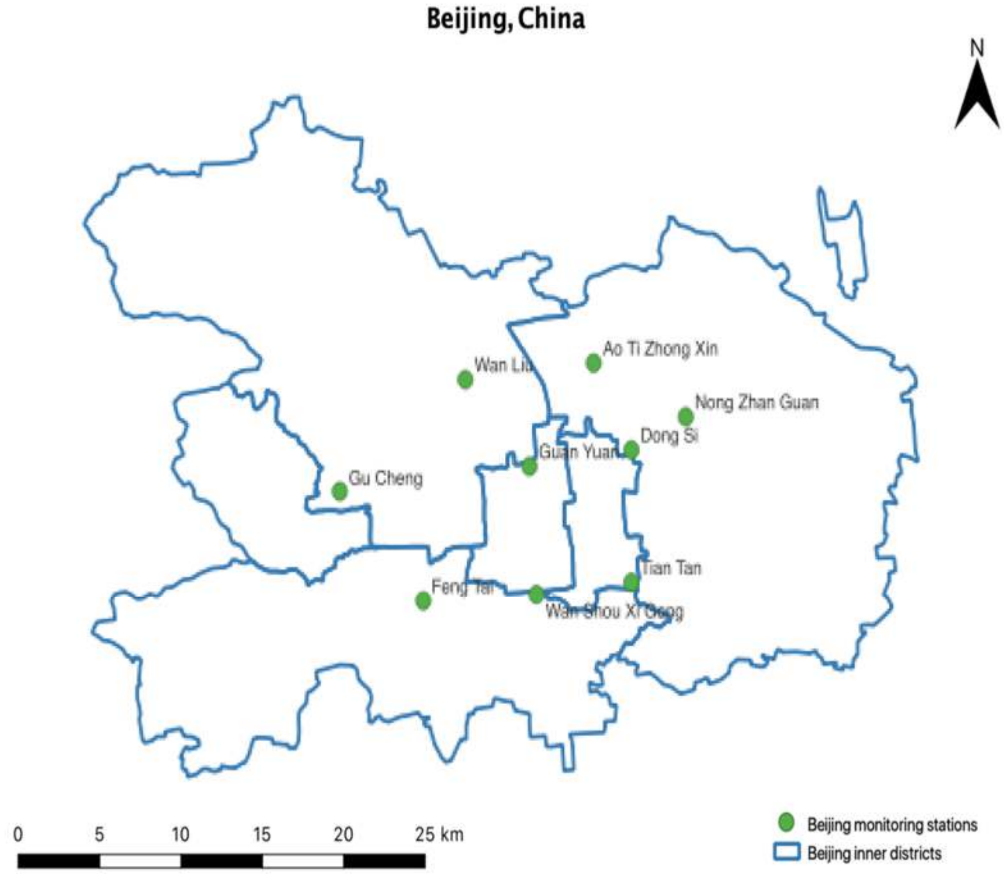
Weitekamp, Chelsea A., and Hans A. Hoffmann. 2021. “Effects of Air Pollution Exposure on Social Behavior: A Synthesis and Call for Research.” *Environmental Health*, 20 (72), https://doi.org/10.1186/s12940-021-00761-8

World Health Organization. 2021. *WHO Global Air Quality Guidelines. Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*. Geneva: World Health Organization.

Zhang, Weifang, Sihui Peng, Jialu Fu, Ke Xu, Huihui Wang, Yu Jin, Tingzhong Yang, and Randall R. Cottrell. 2021. “Urban Air Pollution and Mental Stress: A Nationwide Study of University Students in China.” *Frontiers in Public Health*, 9, doi:10.3389/fpubh.2021.685431. PMID: 34277548; PMCID: PMC8283526.

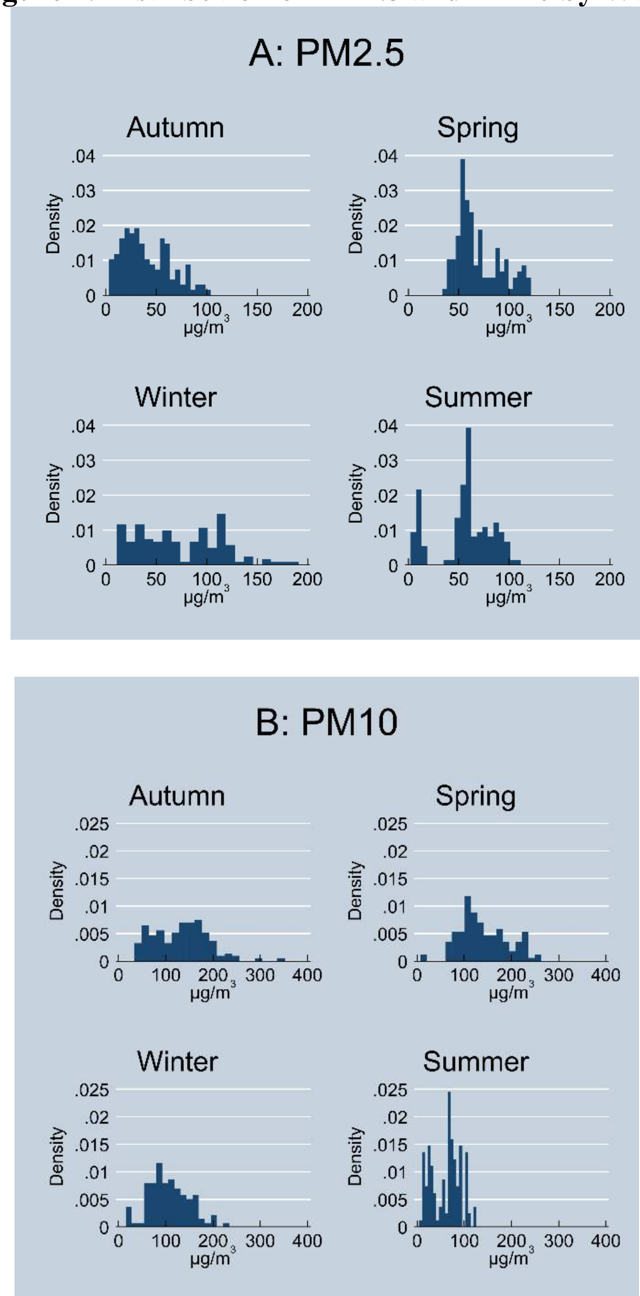
Zhang, Xin, Xi Chen, and Xiaobo Zhang. 2018. “The Impact of Exposure to Air Pollution on Cognitive Performance.” *Proceedings of the National Academy of Sciences* 115 (37): 9193-9197.

Figure 1. Air Pollution Monitoring Stations in Beijing



Notes: The dots indicate the locations of the air pollution monitoring stations. The top map only plots the six districts in the inner city of Beijing where we conducted the experiment.

Figure 2. Distribution of PM2.5 and PM10 by Wave

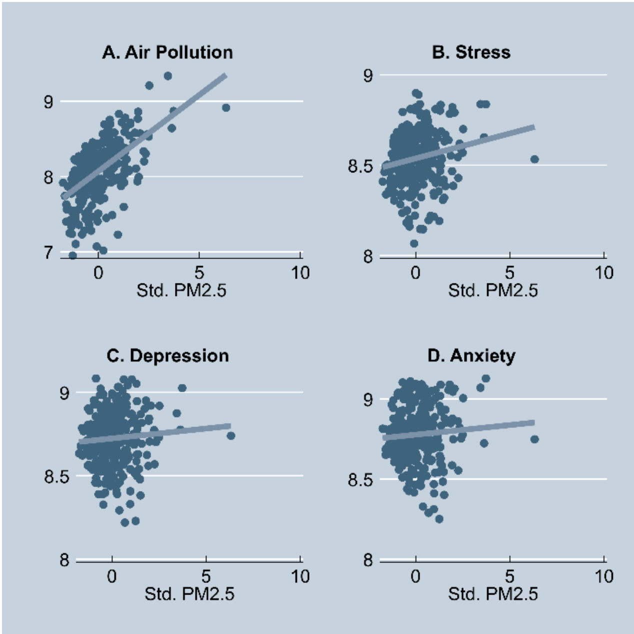


Notes: The distributions show the concentration readings of PM2.5 and PM10 matched with the letters dropped in each wave. Not to be confused with the actual distribution in each season.

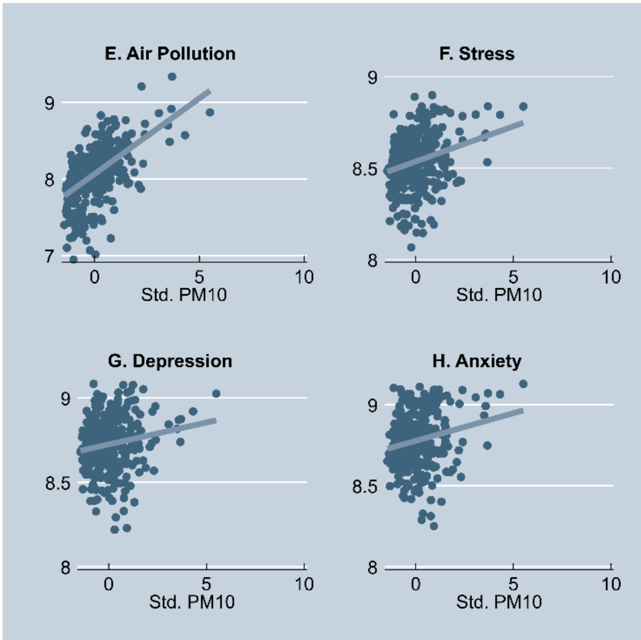
Source: Authors' collection of readings recorded by the nine nearby air pollution monitoring stations in Figure 1.

Figure 3. Baidu Searches Against PM2.5 and PM10 in 4 Major Chinese Cities

Panel A. PM2.5



Panel B. PM10



Notes: The 4 major cities include Beijing 北京, Shanghai 上海, Guangzhou 广州 and Shenzhen 深圳. Numbers on each vertical axis represent the natural log of weighted index of monthly search interest of each Chinese term during 2017-2023. The corresponding Chinese characters are as follows: air pollution 空气污染, stress 压力, anxiety 焦虑, and depression 抑郁. The horizonal axis indicates the standardized PM2.5 in Panel A and the standardized PM10 in Panel B.

Source: Search data are from Baidu Index https://index.baidu.com/v2/index.html#/. PM2.5 and PM10 concentration are from World Air Quality Index Project https://aqicn.org/historical/#city:beijing.

Table 1. Summary Statistics				
	Obs	Mean	Median	Std. Dev.
	(1)	**(2)**	**(3)**	**(4)**
Letter picked up	1,619	0.72	1	0.45
Letter posted	1,619	0.36	0	0.48
Time (minutes)	1,619	5.59	5	3.49
PM2.5 ($\mu g/m^3$)	1,619	59.91	57.44	32.25
PM10 ($\mu g/m^3$)	1,508	109.79	103.49	56.54
Passersby	1,619	28.14	22	23.77
Male	1,619	13.96	11	11.69
Female	1,619	14.19	11	12.66
Ambient noise (decibel)	1,619	67.69	71.20	10.12
Ambient temperature (°C)	1,619	18.32	24	11.39
Surface specific humidity	1,619	0.00620	0.00460	0.00454
Surface wind speed (m/s)	1,619	4.310	3.607	2.377
Surface pressure (Pa)	1,619	98,931	98,664	820.4
Thermal inversion	1,619	0.07	0	0.25
Temperature difference conditional on inversion	112	-1.562	-1.562	0.999

Notes: Time refers to the time interval between the moment the letter was dropped on the ground and the moment it was picked up, or the end of 10 minutes if it was not yet picked up. Passersby include all people who passed by the letter during this period and the person who picked up the letter. Thermal inversion is a dummy variable indicating the lowest inversion occurred at an altitude lower than 320 meters. Temperature difference is the temperature at the bottom of the lowest inversion layer minus the temperature at the top of the layer.

Sources: Data on surface specific humidity, surface wind speed, surface pressure and thermal are acquired from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) from the Global Model and Assimilation Office (GMAO) at National Aeronautics and Space Administration (NASA). PM2.5 and PM10 data are from the air pollution monitoring stations in Beijing. All other variables are authors' own collection in the experiment.

Table 2. OLS Estimates of the Linear Particulate Matters Effects

	(1)	(2)
Std. PM2.5	0.010	
	(0.015)	
Std. PM10		0.039**
		(0.017)
Ambient noise (decibel)	-0.000	0.001
	(0.001)	(0.001)
Ambient temperature (°C)	-0.003	-0.002
	(0.005)	(0.005)
Surface wind speed (m/s)	-0.007	-0.009
	(0.008)	(0.007)
Surface specific humidity	-17.357*	-18.659**
	(9.206)	(8.848)
Surface pressure (Pa)	0.000	0.000
	(0.000)	(0.000)
Passersby per minute	0.013***	0.013***
	(0.005)	(0.005)
% Female passersby	0.001	0.001
	(0.001)	(0.001)
Location fixed effect	Yes	Yes
Wave fixed effect	Yes	Yes
Clusters	539	502
Observations	1,619	1,508

Notes: The dependent variable is a dummy variable indicating whether the letter was posted. The particulate matter variables are the standardized PM2.5 and PM10. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 3. OLS Estimates of the Nonlinear Particulate Matters Effects		
	(1)	(2)
Std. PM2.5		
3rd Quartile	0.002	
	(0.033)	
4th Quartile	0.009	
	(0.033)	
Std. PM10		
3rd Quartile		0.104***
		(0.036)
4th Quartile		0.114***
		(0.040)
Ambient noise (decibel)	-0.000	0.001
	(0.001)	(0.001)
Ambient temperature (°C)	-0.003	-0.002
	(0.005)	(0.005)
Surface wind speed (m/s)	-0.008	-0.007
	(0.008)	(0.008)
Surface specific humidity	-16.110*	-19.896**
	(9.234)	(8.962)
Surface pressure (Pa)	0.000	0.000
	(0.000)	(0.000)
Passersby per minute	0.013***	0.013***
	(0.005)	(0.005)
% Female passersby	0.001	0.001
	(0.001)	(0.001)
Location fixed effect	Yes	Yes
Wave fixed effect	Yes	Yes
Clusters	539	502
Observations	1,619	1,508

Notes: The dependent variable is a dummy variable indicating whether the letter was posted. The particulate matter variables are two dummy variables indicating the third and fourth quartile of the standardized PM2.5 and PM10 with the first and second quartile as the reference group. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 4. Comparison of the Linear Effects of Particulate Matters between Weekdays and Weekends

	(1)	(2)
Std. PM2.5	0.016	
	(0.018)	
Std. PM10		0.028
		(0.022)
Weekend	0.043	0.040
	(0.035)	(0.038)
Std. PM2.5 × Weekend	-0.016	
	(0.026)	
Std. PM10 × Weekend		0.009
		(0.026)
Ambient noise (decibel)	-0.000	0.001
	(0.001)	(0.001)
Ambient temperature (°C)	-0.004	-0.002
	(0.005)	(0.005)
Surface wind speed (m/s)	-0.004	-0.006
	(0.008)	(0.008)
Surface specific humidity	-13.332	-14.675
	(9.657)	(9.518)
Surface pressure (Pa)	0.000	0.000
	(0.000)	(0.000)
Passersby per minute	0.013***	0.013***
	(0.005)	(0.005)
% Female passersby	0.001	0.001
	(0.001)	(0.001)
Location fixed effect	Yes	Yes
Wave fixed effect	Yes	Yes
Clusters	539	502
Observations	1,619	1,508
Weekend Obs	30%	31%

Notes: The dependent variable is a dummy variable indicating whether the letter was posted. Weekend is a dummy variable indicating that the experiment was carried out during weekend. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.

Table 5. 2SLS Estimates of the Linear Effect of Particulate Matters

	(1)	(2)	(3)	(4)
	Panel A: Second Stage Results			
Std. PM2.5	0.220**	0.163***		
	(0.095)	(0.059)		
Std. PM10			0.129**	0.141***
			(0.051)	(0.048)
	Panel B: First Stage Results			
Inversion	0.702***	1.852***	1.180***	1.698***
	(0.137)	(0.175)	(0.137)	(0.269)
Temperature difference		0.750***		0.338***
		(0.087)		(0.115)
Kleibergen-Paap *F* stat	12.97	65.89	60.31	36.59
p-value for Hansen *J* stat		0.417		0.436
Clusters	539	539	502	502
Observations	1,619	1,619	1,508	1,508

Notes: The dependent variable is a dummy variable indicating whether the letter was posted in Panel A. In Panel B, the dependent variable is Std. PM2.5 in column (1) and (2) and Std. PM10 in column (3) and (4). Thermal inversion in Panel B is a dummy variable indicating whether thermal inversion occurred at the altitude of 320 meter or below; the change in temperature is the difference between the temperature at the top and bottom of the inversion layer. All regressions additionally control for ambient noise, temperature, passersby per minute, share of female passersby and a full set of location and wave fixed effects. Robust standard errors clustered at location-date-hour level are in parentheses. ***, ** and * indicate statistically significant at 1%, 5%, and 10%, respectively.